Analysis and comparison of vacant land resources for urban food production

A chapter from the Masters thesis

Borrowed Ground:
Evaluating the Potential Role of Usufruct in Neighborhood-Scale Foodsheds

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2.1 Introduction

As concerns about climate change, sustainability, and food insecurity have come to the forefront of conversations about our food system, scholars, practitioners, and policymakers have explored the extent to which cities might feed themselves. Urban agriculture can expand food access in cities, engage urban dwellers in food production, and provide a beneficial use for unused urban lots. Idle or vacant land, both publicly and privately owned, represents an important resource for urban gardeners and farmers, and potentially for their rural counterparts as well. Applying the concept of usufruct, or productively using another's unused land, could increase agricultural use of both privately and publicly owned land resources. But little is understood about how these land resources vary according to degree of urbanization or ownership.

Urban land inventories identify and assess vacant land resources with potential for urban food production. This approach typically begins with identification of vacant parcels and then applies a series of criteria to these parcels to assess their suitability for urban agriculture. Land inventories have been conducted in Portland (Balmer et al., 2006), Seattle (Horst, 2008), Vancouver (Kaethler et al., 2010), Madison (Eanes, 2012), Oakland (McClintock et al., 2010), and Toronto (MacRae et al., 2010). Most of these inventories were meant to pursue a practical rather than scholarly goal, and in the cases of Portland and Vancouver succeeded in integrating considerations for urban agriculture into their respective city planning processes (Mendes et al., 2008).

Land inventories have typically either focused exclusively on publicly owned land (Balmer et al., 2006; Horst, 2008; McClintock et al., 2010) or have failed to differentiate between public and private ownership (MacRae et al., 2010). While privately owned land is likely to be much more plentiful than publicly owned land (Colasanti and Hamm, 2010; Urban Design Lab at the Earth Institute, 2011), it carries with it certain implications about usufruct agreements for food production. Whereas public entities usually have formalized processes for allowing use of their land, agreements between private landowners and “borrowers” of their land range from non-existent to formal, with many informal arrangements in between. Land inventories that incorporate more detailed considerations of public vs. private ownership may help guide policy to expand and develop urban food production.

This chapter evaluates and compares the characteristics of vacant land resources according to ownership and urbanization. Neighborhood-scale (300-meter radius) study sites were selected in seven central Ohio counties representing 4 categories of quantified urbanization, and vacant parcels were identified within each study site. A composite land suitability index was created based on solar exposure, soil quality, slope, and water access, and this suitability index was applied to the vacant land within each study site. Spatial characteristics of parcels, total land area per study site, and the suitability of vacant parcels were compared between public and private ownership and among the four urbanization categories.

2.2 Methods

Figure 2.1 provides an overview of the methods described below.

2.2.1 Study area: Central Ohio

Seven counties in central Ohio were selected for this study: Delaware, Fairfield, Franklin, Licking, Madison, Pickaway, and Union. These counties, along with Morrow (which was not included in this study) make up the Columbus Metropolitan Statistical Area (MSA). Columbus is Ohio’s capital, the largest city, and home to The Ohio State University. Unlike Ohio’s two other major cities, Cleveland and Cincinnati, Columbus has been steadily gaining population for the past half century. For this reason, Columbus offers a contrast to vacant land research that has focused on shrinking cities with vast vacancies, such as Detroit and Buffalo. The Columbus

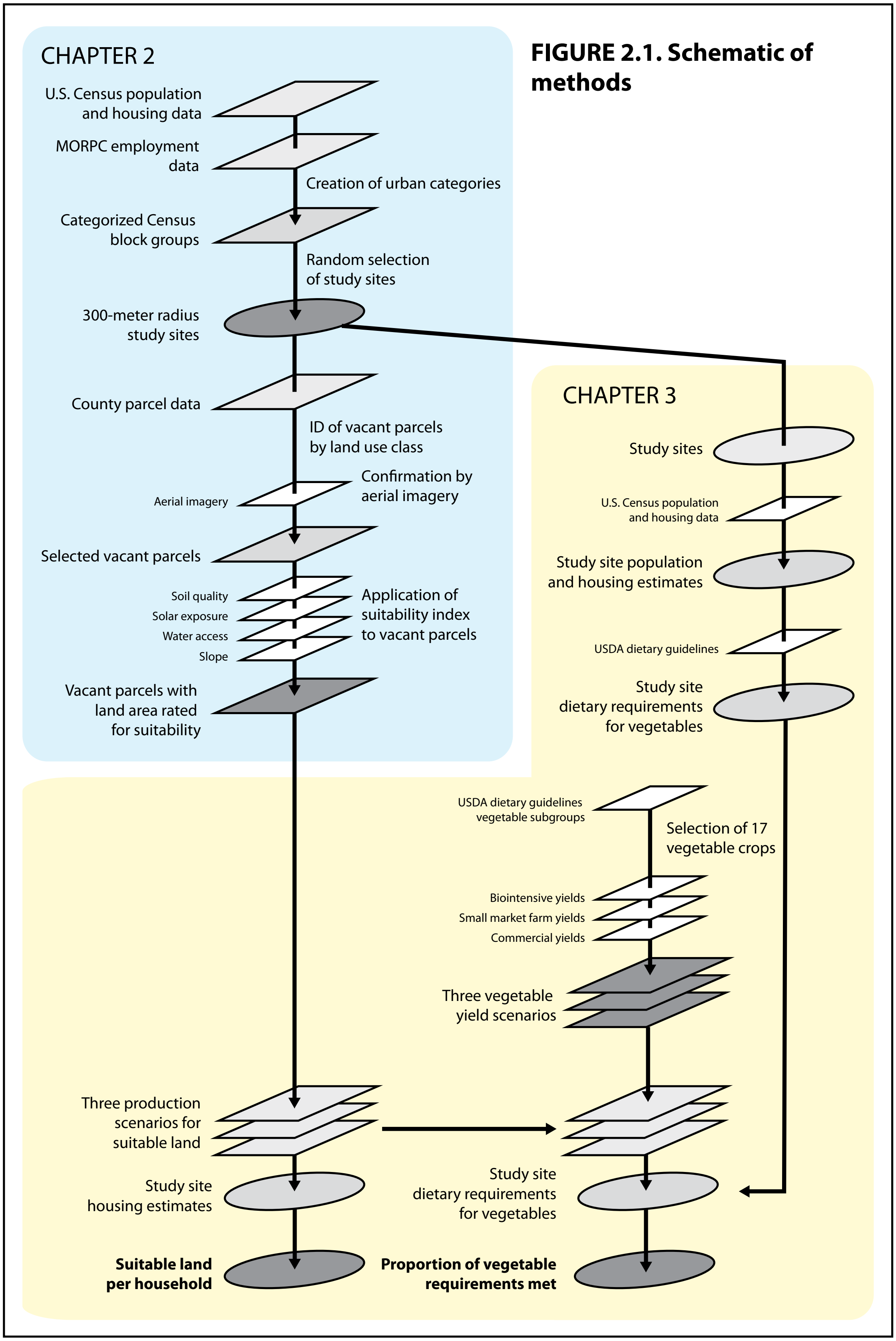


FIGURE 2.1. Schematic of methods

MSA population grew 6.2% from 2004 to 2009—higher than the average rate of 5.4% for the 100 largest MSAs in the U.S. (Community Research Partners, 2011). Of the cities where land inventories have been conducted, Indianapolis and Portland have the most in common with Columbus in terms of population growth and density; however, studies in these cities did not compare public or private ownership or assess urbanization. Central Ohio thus provides an opportunity to better understand the dynamics of vacant land resources in growing U.S. metropolitan areas. Figure 2.2A shows the location of the study area, and Table 2.1 provides basic population statistics for the seven counties.

2.2.2 Creation of urbanization categories

Urban gradient analysis evaluates how various factors, such as population density, spatial pattern, land use, or impervious surface cover, change progressively and predictably

TABLE 2.1. Study Area Population By County

County	2010 Population	Population Per Sq. Mile	2000-2010 Growth
Delaware	174,214	393.2	+58.4%
Fairfield	146,156	289.8	+19.1%
Franklin	1,163,414	2,186.1	+8.8%
Licking	166,492	243.9	+14.4%
Madison	43,435	93.2	+8.8%
Pickaway	55,698	111.1	+5.6%
Union	52,300	121.1	+27.8%

from less urban to more urban environments (Alberti, 2008, 2005; Breuste et al., 2008; Hahs and McDonnell, 2006; McDonnell and Hahs, 2008). Selected factors can be reduced to a single gradient using Principal Components Analysis (PCA), and the resulting gradient can be used as an independent variable in studying additional factors (Alberti, 2008; Hahs and McDonnell, 2006). For this research, population density, housing density, and employment density were used to create a 2-factor PCA, which was the basis for a k-means cluster analysis. This cluster

FIGURE 2.2A. Study area and urbanization categories

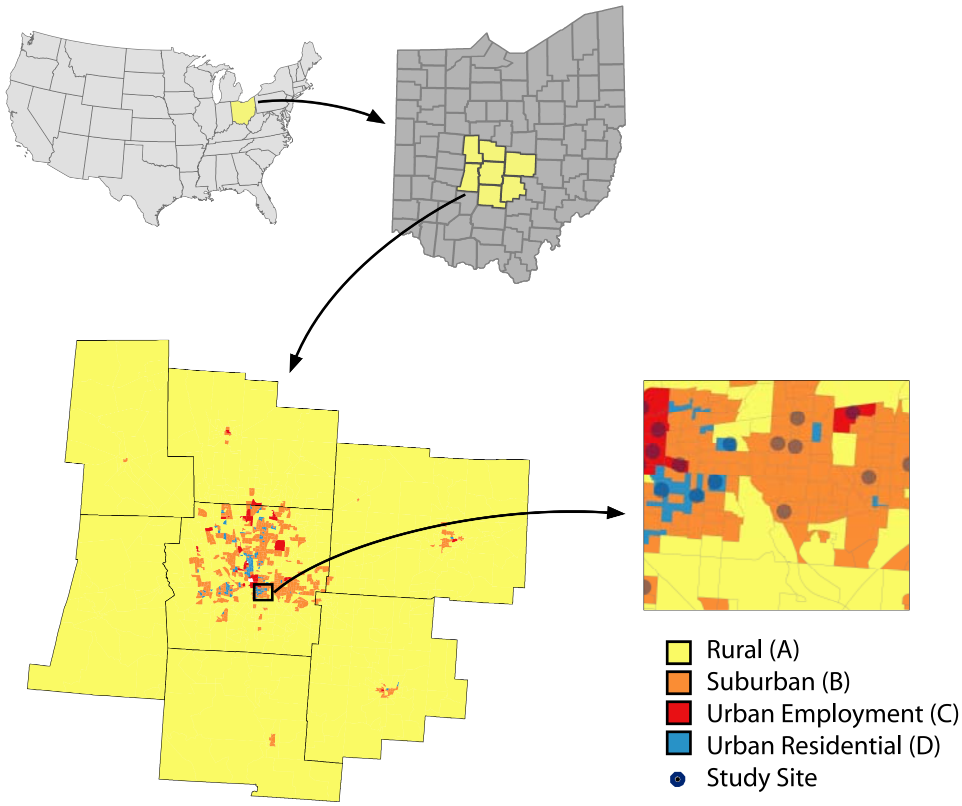
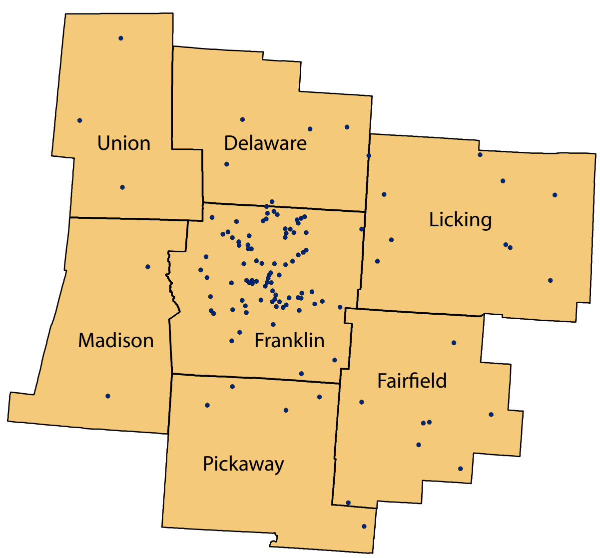


FIGURE 2.2B. Study area and study sites



analysis sorted U.S. Census block groups into 4 discrete categories of urbanization. Figure 2.2A illustrates the urbanization zones.

U.S. Census Bureau 2010 Decennial Census block group-level population and housing data were acquired from the Mid-Ohio Regional Planning Commission (MORPC), as were proprietary 2010 employment point data aggregated by MORPC to a ¼-mile grid (Mid-Ohio Regional Planning Commission, 2010a; U.S. Census Bureau, 2010). U.S. Census employment data was not yet available for 2010. Job totals were redistributed from the MORPC ¼-mile grid to census block group geographies in ArcMap 10.1 (ESRI, 2012) using a basic areal weighting method (Yale University, 2007). ArcMap's "Calculate geometry" function was used to calculate the area in hectares of each block group, and the population, housing, and employment totals were divided by this area to calculate densities for each block group in terms of persons, housing units, or jobs per hectare.

The data table with these densities was imported to SYSTAT 13.1 (Systat Software, Inc., 2012). PCA with two factors was used to analyze the three density variables for population, housing, and employment. The resulting 2 factors explained slightly more than 96% of the total variance. Based on the component loadings, Component 1 generally corresponds (positively) to population and housing, while Component 2 generally corresponds (negatively) to employment. K-means cluster analysis was applied to the standardized PCA factor scores to group census blocks into seven clusters. The spatially fine gradations in resulting clusters would have made sampling with 300-meter study sites problematic, so some of the seven clusters were combined based on interpretation of their PCA scores. Cluster 1 block groups were designated as urban category A; Cluster 2 block groups were designated as urban category B; Clusters 3 and 4 were combined to form urban category C; and Clusters 6 and 7 were combined to form urban category D. Cluster 5 was omitted because it only contained two block groups. Table 2.2 shows descriptive statistics for each designated category in terms of the original three variables of population, housing and employment density, as well as a descriptive name based on these variables. For ease of interpretation, henceforth these categories will be referred to as Rural (A), Suburban (B), Urban Employment (C), and Urban Residential (D).

TABLE 2.2. Urbanization Categories

	Jobs per hectare	Population per hectare	Housing units per hectare	Description
Category A	2.9 +/- 4.4	5.4 +/- 4.5	2.3 +/- 2.0	Rural
Category B	4.3 +/- 4.4	21.5 +/- 5.4	9.9 +/- 2.8	Suburban
Category C	61.5 +/- 50.0	17.4 +/- 14.4	7.8 +/- 6.1	Urban Employment
Category D	6.4 +/- 7.0	51.1 +/- 29.8	23.9 +/- 9.6	Urban Residential

2.2.3 Study site selection

Randomly sampled study sites of 300-meter radius were selected within each of the four urban categories. A distance of ¼-mile is often used in urban planning parlance as a proxy for "walking distance"; however, study sites with ¼-mile radii were in some cases too large to represent census block groups, so the slightly smaller size of 300-meter radius was selected. To minimize inclusion of bordering urban categories in sample sites, each category zone was reduced in size by a 200-meter interior buffer created along each category's boundary. The "Create random points" tool was used to generate 30 random points separated by at least 600 meters (to prevent overlapping 300-meter buffers) in the Rural and Suburban categories. The limited extent of the Urban Employment and Urban Residential categories did not allow the same approach, however, because the "Create random points" tool was unable to generate points at the necessary density. Instead, the tool was used to place one point randomly within each Urban Residential block group not eliminated by the boundary buffer. All points that were more than 600 meters from the nearest point were kept. The remaining points were manually edited by a process of selecting a point at random, deleting all points within 600 meters, selecting another point just beyond 600 meters of the first, and repeating the process. A dense coverage of random points all separated by at least 600 meters resulted. This process was repeated for the Urban

Employment category, but because this category's block groups were larger, three random points were initially created within each block group. After all points for all categories were finalized, these points were given a 300-meter buffer to establish study sites. Two Urban Employment sites located on Ohio State University's main campus were omitted. In spite of the 200-meter interior buffer created for each zone, some study sites occurring near the boundary of their zone included portions of neighboring categories. Percentage composition of each site was calculated to confirm that sites were composed of at least 70% of the category they were representing. This process resulted in many more Urban Residential sites than the other categories. A random number generation code (Iowa State University, 2012) was used to assign a random value to each Urban Residential site. Sites were then sorted by this value and the sites with the 17 lowest values were omitted, with the exception of two sites located outside of the central footprint of Columbus. These were preserved because all other Urban Residential sites were located within the footprint of Columbus. An additional Suburban site was ultimately deleted because no parcel data was available for that area. This process resulted in the following number of study sites per urban category:

Rural (A): 30

Suburban (B): 29

Urban Employment (C): 25

Urban Residential (D): 32

Total: 116 study sites

Figure 2.2B illustrates the location of study sites within the study area.

2.2.4 Identification of vacant parcels

County parcel data was acquired from each of the seven counties (Delaware County Auditor, 2012; Fairfield County, 2012; Franklin County, 2012; Licking County, 2012; Madison County, 2012; Pickaway County, 2012; Union County, 2012). All parcels that overlapped study sites were extracted using ArcMap's "Spatial Join" tool, resulting in a separate shapefile for each relevant combination of county and urban category. A field denoting vacancy status was created in each attribute table, and each parcel was classified as vacant or non-vacant based on its land use class. Some vacant land use classes were omitted (classified as non-vacant): agricultural vacant land was omitted because it was assumed already to be in production, and industrial vacant land was omitted because of soil contamination concerns. Parcels classified as rights-of-way or lacking any land use class were also omitted. Some land uses did not denote vacancy status, such as "Owned by County," "Zero valued parcels," and any "Exempt" land use. These were all designated as "TBD" for later assessment using aerial imagery. Franklin County's parcel data has two attributes relevant to vacancy status: land use class and property type. When these attributes agreed, the parcel in question was designated as either vacant or non-vacant. When land use class indicated one status and property type indicated another, that parcel was also designated as "TBD".

Aerial imagery for each county was acquired from the Ohio Statewide Imagery Program (Ohio Statewide Imagery Program, 2006a, 2006b, 2006c, 2006d, 2006e, 2006f, 2006g). All parcels previously designated with "TBD" vacancy status were visually assessed on the basis of aerial imagery. Google Maps and Google Street View were also occasionally consulted (Google, 2013). Parcels that appeared to be entirely free of structures and not currently in use (as parking lots, for example) were classified as vacant, and all others were classified as non-vacant.

Some individual parcels were composed of non-contiguous separate fragments, some of which were located entirely outside of study site boundaries. ArcMap's "Multipart to single part" operation was used to disaggregate these parcels, and outlying fragments were deleted.

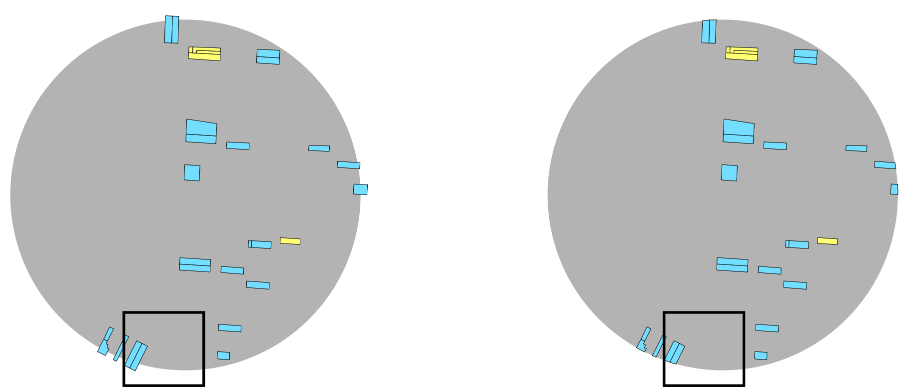
All parcels that had thus far been classified as vacant were given a final assessment using aerial imagery. This led to a 10.3% reduction in the number of parcels classified as vacant, ultimately resulting in 696 parcels being included in the subsequent analysis. No study sites in Madison, Pickaway, or Union counties contained any vacant parcels, so the subsequent analysis was conducted on vacant land in Delaware, Fairfield, Franklin, and Licking counties.

A field denoting public or private ownership was created and populated with "Public" or "Private" based on the owner name of each parcel. Parcels owned by public entities (city, county, or state) were classified as publicly owned and all others were classified as privately owned.

Spatial characteristics of whole vacant parcels (including contiguous portions lying outside of study site boundaries) were calculated in the ArcMap attribute tables. Fields were added for parcel area and perimeter and calculated using the "Calculate Geometry" tool. A third field for perimeter-area ratio (PAR) was calculated using the following equation: PAR = Perimeter / √(Parcel area).

Parcels were then clipped to study site boundaries. Subsequent land suitability assessment was only performed for the portions of parcels lying within study site boundaries. Figure 2.3 illustrates whole vs. clipped parcels in an example study site.

FIGURE 2.3. Study site with whole and clipped parcels



2.2.5 Land suitability index

Four factors were selected to assess vacant parcels for vegetable production suitability. Selection was based on existing land inventory methods, conversations with practitioners, and available data. These factors were soil quality, slope, solar exposure, and access to water.

- Soil quality

Although quality of in situ soils has not been included in urban land inventories to date, it is a key consideration for gardeners and farmers, particularly those cultivating borrowed land. Usufruct agreements often imply a limited or uncertain tenure, and the time and financial investment of improving soils may be disincentive if use of a parcel will be short-lived. Urban soils tend to be heavily disturbed and highly variable, with compaction, lack of organic matter, and poor drainage being the key obstacles to vegetable production (Beniston and Lal, 2012). Accurate assessment of these and other characteristics is difficult without performing on-site soil tests of parcels. The Soil Survey Geographic (SSURGO) database, though extensive and detailed, lacks high resolution in urban contexts (Shuster et al., 2011). It is, however, the most detailed soil database available, and is used in this research as a broad indicator of potential in situ soil quality.

SSURGO data for each county was downloaded from the USDA Soil Data Mart (Natural Resources Conservation Service, United States Department of Agriculture, 2012a, 2012b, 2012c, 2012d, 2010a, 2010b, 2010c). SSURGO data has two components: the spatial soil map, which is composed of polygon soil map units, and the soil survey attribute database. The Soil Data Viewer (Natural Resources Conservation Service, United States Department of Agriculture, 2011) is a free, publicly available add-in extension for ArcMap that allows integration of the attribute database with the spatial soil map units in the ArcMap environment. This tool was used to query and process soil attributes for this analysis.

A composite soil quality rating was developed based primarily on the Cornell Soil Health

Assessment Training Manual (SHATM), which rates soils based on 12 indicators grouped into three equally weighted categories: physical, biological, and chemical (Gugino et al., 2009). Because only some of these indicators were available in the SSURGO dataset, the rating system used was simplified from the Cornell SHATM, with one indicator from each category, as well as an additional attribute for drainage class, as follows:

- Physical: Available water capacity (AWC)
- Biological: Percent organic matter (OM)
- Chemical: pH
- Drainage class

Some of the soil map units in the SSURGO database lacked values for these attributes. This incomplete data was remedied in one of two ways: (1) attributes were transferred from a map unit of the same soil type found in another county (e.g. Franklin County map unit CfB was given the attributes of Fairfield County map unit CfB); or (2) attributes were transferred from a corresponding soil type elsewhere within the same county (e.g. Cardington Urban soils – CbB – were given the attributes of other Cardington soils – CaB – found elsewhere in the same county). In this way, all soil map units were assigned attributes for the four soil quality indicators, with the exception of Udorthents, or imported fill soils, and gravel quarry/pits.

For AWC, OM, and pH, scoring functions provided by the Cornell SHATM were used to rate each indicator value into three tiers, with 3 being the highest (or best) and 1 being the lowest. The tier thresholds for AWC and OM were determined by texture class. Drainage class ratings were also grouped into three categories. Indicator values are specified in Table 2.3.

After each of the four indicators was given a 1-3 rating, these ratings were combined using a weighting system based on Vadrevu et al.'s (2008) Agroecosystem Health Index (AHI). In the AHI, soil is rated according to seven attributes: soil organic matter (%), available water capacity (%), pH, erosion factor, land capability class, farmer's reliance on fertilizer, and farmer's reliance on herbicides. Each indicator was assigned a weight based on the input of experts in an analytical hierarchy process. The relative weights for AWC, OM, and pH from Vadrevu et al. (2008) were used for this 4-indicator system, and drainage class was assigned the same weight as AWC. Indicators were thus weighted as follows: AWC (21.22%), drainage class (21.22%), OM (40.95%), and pH (16.61%). A composite soil quality rating was calculated for

TABLE 2.3A. Available Water Capacity (m/m) Rating Scheme

	Coarse	Medium	Fine
Rating 1	< 0.096	< 0.134	< 0.142
Rating 2	0.096-0.164	0.134 - 0.186	0.142 – 0.217
Rating 3	> 0.164	> 0 .186	> 0.217

TABLE 2.3B. Percent organic matter (%) Rating Scheme

	Coarse	Medium	Fine
Rating 1	< 2.34	< 2.85	< 3.54
Rating 2	2.34 – 3.85	2.85 – 4.15	3.54 – 4.75
Rating 3	> 3.85	> 4.15	> 4.75

TABLE 2.3C. pH Rating Scheme

Rating 1	< 5.7 ; > 7.6
Rating 2	5.7 – 6.1 ; 7.5 – 7.6
Rating 3	6.2 – 7.4

TABLE 2.3D. Drainage Class Rating Scheme

Rating 1	Poorly drained; very poorly drained
Rating 2	Somewhat poorly drained
Rating 3	Moderately well drained; well drained

each map unit using these weights. Udorthents soils and gravel/quarry pits, which did not have values for the four indicators, were assigned the lowest possible score of "1."

- Slope

Farms and gardens require a relatively level surface for normal production practices. In land inventories for Portland and Oakland, Balmer et al. (2006) and McClintock et al. (2010) used Digital Elevation Model (DEM) data to model slopes in ArcMap. "Level" parcels were those under 4% or 5% slope, while the 5-10% slope range was considered feasible but less optimal. Slope assessment methods and ratings used in this research were based on these studies.

ESRI GRID Digital Elevation Model (DEM) Mosaic data was downloaded for each county (Ohio Statewide Imagery Program, 2006h, 2006i, 2006j, 2006k, 2006l, 2006m, 2006n). ArcMap's "Slope" tool was used to generate slope TIFF files for each study site using the same cell size as the DEM mosaics (2.5-foot). Percent slope values were then reclassified to a 3-tier rating with 0-5% slopes rated "3", 5-10% slopes rated "2", and slopes above 10% rated "1".

- Solar exposure

Most vegetable crops need ample direct sunlight to provide good yields; eight hours per day during the growing season has been identified as a reasonable goal (Cleveland Urban Design Collaborative, 2008; Eanes, 2012). This can be a challenge for urban vegetable growers because of the shading effects of the built environment and the tree canopy. Light Detection and Ranging (LIDAR) data provide a potential avenue for modeling solar exposure to assess a parcel's suitability for vegetable production. LIDAR measures surface elevation at a high sampling density, capturing the morphology of tree canopy, buildings, and other structures. Yu et al. (2009) used LIDAR data to model solar radiation in downtown Houston at 10-minute intervals, and Nipen (2009) used a much simpler LIDAR-based model to assess suitability of land on the Halifax peninsula for urban agriculture. This research used a solar modeling approach somewhat simplified from the approach of Yu et al.'s, but more extensive than Nipen's.

Individual LIDAR data tiles corresponding to the study sites were downloaded from the Ohio Statewide Imagery Program (Ohio Statewide Imagery Program, 2006o). Tiles were converted to TIFF format, and ArcMap's "Hillshade" tool was used to model sun and shade accounting for the azimuth and altitude of the sun. Shade was modeled for every hour of every day for 21 full weeks starting with the estimated last spring frost date to the end of the week of the estimated first autumn frost. Assuming 2012 dates, this means that the model was run from Wednesday, May 9 to Tuesday, October 2. The resulting rasters were averaged by day to generate a final single raster of average hours of sun per day during the growing season. Raster cells were given a binary rating designating whether they received 8 or more hours of sun per day on average.

- Access to water

Access to water is a key consideration for gardeners and farmers in urban settings, since most common vegetable and fruit crops require irrigation. Land inventories in Portland, Indianapolis, Madison, and Oakland all included water access as a criterion for parcel suitability (Balmer et al., 2006; Carter and Anderson, 2012; Eanes, 2012; McClintock et al., 2010). In this research, a binary water access rating was based on parcel data when available. Franklin County parcel data included an attribute for "public water," however, Delaware, Fairfield, and Licking county parcels lacked such an attribute. Parcels in these counties were assumed to have water access if they fell within the boundaries of a municipality, based on a shapefile of municipal boundaries acquired from MORPC (2010b). Parcels that did not fall within municipal boundaries were assumed to not have access to water.

- Five-tier land suitability index

The ratings for soil quality, slope, solar exposure, and access to water were processed to create five tiers of land that would be suitable for vegetable production under different assumptions of improvement. Only land receiving eight or more hours of sun per day on average during the growing season was included. Tier 1 land was assumed to require no improvement at all: in addition to receiving necessary sun, it had soils rated 2.25 or higher, slopes under 5%, and access to water. Soil amendment is a common improvement activity undertaken by urban gardeners and farmers (Carter and Anderson, 2012), so the next tiers assumed increasing levels of soil improvement. Tier 2 included soils rated 1.75 or higher, and Tier 3 included all soils. Rainwater catchment structures are a solution for land without access to water; this level of investment was assumed for Tier 4, which included land meeting the previous criteria whether or not it had access to water. Tier 5 land assumed landscaping to level moderate slopes, and included land meeting the previous criteria with up to 10% slopes. These five tiers exclude any land not receiving eight hours of sun or with slopes over 10%. These tiers were processed in ArcMap as a 2m-cell raster that combined slope and solar exposure ratings and were clipped by the parcel and soil polygons depending on the tier criteria. Table 2.4 summarizes the characteristics of these tiers. Figure 2.4 illustrates the suitability tiers in example study sites from each of the four urban categories, and Figure 2.5 demonstrates the suitability rating process.

TABLE 2.4. Land Suitability Tiers

	Soil Quality	Water Access	Slope	Average sun
Tier 1	2.25+_	Yes	<5%	8+ hours/day
Tier 2	1.75+	Yes	<5%	8+ hours/day
Tier 3	1.0+ (all)	Yes	<5%	8+ hours/day
Tier 4	1.0+ (all)	No	<5%	8+ hours/day
Tier 5	1.0+ (all)	No	<10%	8+ hours/day

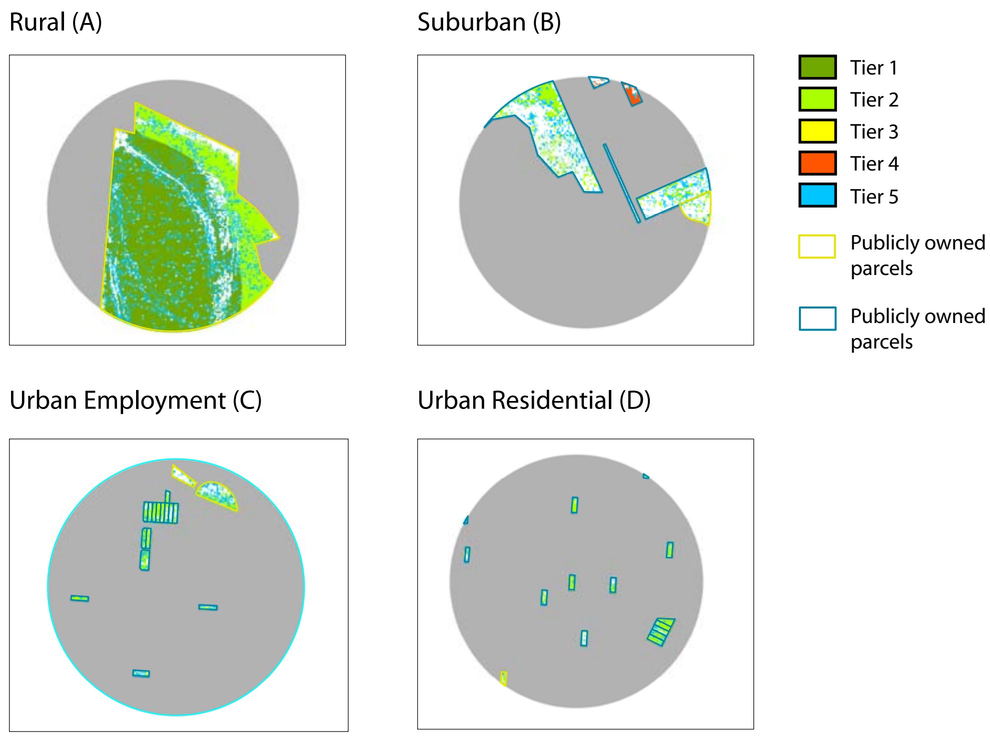
2.2.6 Calculation of study site characteristics

The following characteristics were calculated for each of the 116 study sites:

- Mean parcel size (in terms of area): publicly owned, privately owned, and combined.
- Mean perimeter-area ratio: publicly owned, privately owned, and combined.
- Total vacant area: publicly owned, privately owned, and combined.
- Total area for each tier of land suitability: publicly owned, privately owned, and combined.
- Percent of total vacant land qualifying for each tier of land suitability: publicly owned, privately owned, and combined.

2.2.7 Statistical analysis

FIGURE 2.4. Examples of land suitability ratings by urban category

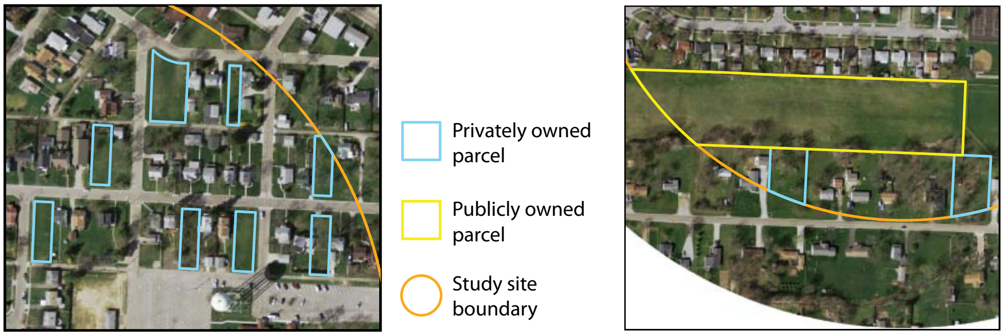


Statistical analysis was performed to test the following null hypotheses:

- H_0: Urbanization has no effect on vacant parcel size, abundance, or quality.
- H_0: Ownership has no effect on vacant parcel size, abundance, or quality.

Many study sites had no vacant land, and many sites with vacant land had no land qualifying for a given suitability tier. These characteristics resulted in non-normal data distribution, which was caused by a large number of zero values. When zero values were excluded, however, and data was transformed, data values were normally distributed. As a result, a mixed model was used: the first part of the model differentiated between zero and non-zero values, and the second part of the model determined the distribution of non-zero values (Hyndman, 2010). Chi-square tests were used to analyze both likelihood of presence of vacant land within each study site and likelihood of presence of land qualifying for each

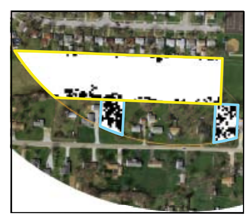
FIGURE 2.5. Example of suitability rating process



LIDAR data was used to model average daily hours of sun during the growing season. The images at left and right show the solar exposure layer with partial transparency.

These images show the solar exposure layer with no transparency. The lighter cells represent higher averages of daily sun.

The solar exposure layer was reclassified to a binary rating. White cells represent areas receiving at least eight hours of sun per day on average, and black cells represent areas receiving less than eight hours.

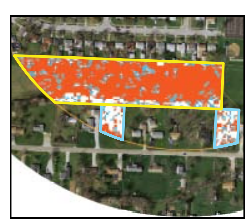


Slopes were calculated using DEM data and reclassified to a three-tiered rating.

- 0-5% slope
- 5-10% slope
- 10+% slope

The slope and solar ratings were combined with rated soil polygons and parcels rated for water access to create a five-tiered rating system. Suitability decreases from 1 to 5. Only ratings 2, 4 and 5 are shown here.

1 2 3 4 5



tier when vacant land is present, according to urbanization category and public or private ownership. Chi-square tests were also used to compare overall distributions of land suitability within each category. ANOVA tests were run on transformed values (Table 2.5 shows types of transformation used) to measure the effect of urbanization category and public or private ownership on each of the calculated study site characteristics. Because only one Rural category study site had a publicly owned parcel, the effect of ownership within the Rural category could not be analyzed, and analysis of the effect of urbanization on publicly owned parcels was limited to the Suburban, Urban Employment and Urban Residential categories. Statistical analysis was performed in SYSTAT 13 (Systat Software, Inc., 2012).

TABLE 2.5. Data Transformations

Variable	Transformation
Mean Parcel Size	Log10(x)
Mean Perimeter-Area Ratio	$1/X^2$
Total Vacant Area	Log10(x)
Scenario (1-5) Area	Log10(x)
Percent Scenario (1-5) Area	arcsine $\sqrt{x}$

2.3 Results

Results for each of the following analyses are summarized in Table 2.6.

2.3.1 Differences between publicly and privately owned land

Results indicate that there are some significant differences in abundance and quality between publicly and privately owned vacant land, and that in some cases these differences depend on the urban context. Publicly owned parcels were found to be larger in the Suburban category ($F_{(1,31)}$=14.073, p=0.001; Fig. 2.6), but this difference did not carry through to more

TABLE 2.6. Summary of Results

Data Restriction	Effect	Chi-square	N	ANOVA F-Ratio	df	p-value
Mean Parcel Size						
None	Urbanization x Ownership		97	4.291	3,89	**0.007**
Publicly-owned B-D only	Urbanization		20	6.838	2,17	**0.007**
Privately-owned	Urbanization		76	6.855	3,72	**0.000**
Category B	Ownership		33	14.073	1,31	**0.001**
Category C	Ownership		26	0.061	1,24	0.807
Category D	Ownership		30	0.031	1,28	0.862
Public/Private combined	Urbanization		79	6.563	3,75	**0.001**
Mean Perimeter-Area Ratio						
None	Urbanization x Ownership		97	0.715	3,89	0.546
None	Urbanization		97	0.106	3,93	0.956
None	Ownership		97	0.191	1,95	0.663
Public/Private combined	Urbanization		79	0.646	3,75	0.588
Presence of Vacant Land						
None	Urbanization	28.233	232		3	**<0.001**
None	Ownership	53.593	232		1	**<0.001**
Public/Private combined	Urbanization	34.679	116		3	**<0.001**
Public/Private combined, B-D only	Urbanization	4.065	86		2	0.131
Total Vacant Area (when present)						
None	Urbanization x Ownership		97	4.363	3,89	**0.006**
Publicly-owned B-D only	Urbanization		20	3.199	2,17	*0.066*
Privately-owned	Urbanization		76	1.010	3,72	0.393
Category B	Ownership		33	0.316	1,31	0.578
Category C	Ownership		26	6.555	1,24	**0.017**
Category D	Ownership		30	10.467	1,28	**0.003**
Public/Private combined	Urbanization		79	0.492	3,75	0.689
Presence of Tier 1 Land						
None	Urbanization	3.904	97		3	0.272
None	Ownership	0.523	97		1	0.470
Public/Private combined	Urbanization	3.762	79		3	0.288
Tier 1 Area (when present)						
None	Ownership		14	4.387	1,12	*0.058*

TABLE 2.6. Summary of Results

Data Restriction	Effect	Chi-square	N	ANOVA F-Ratio	df	p-value
Privately-owned	Urbanization		12	0.730	3,8	0.563
Public/Private Combined	Urbanization		13	1.426	3,9	0.298
Tier 1 Percent of Total Vacant Land (when Tier 1 land is present)						
None	Ownership		14	5.074	1,12	**0.044**
Privately-owned	Urbanization		12	0.730	3,8	0.563
Public/Private Combined	Urbanization		13	0.953	3,9	0.455
Presence of Tier 2 Land						
None	Urbanization	30.841	97		3	**<0.001**
Categories B-D	Urbanization	2.942	89		2	0.230
None	Ownership	0.002	97		1	0.965
Public/Private Combined	Urbanization	32.921	79		3	**<0.001**
Public/Private Combined, B-D only	Urbanization	3.562	71		2	0.168
Tier 2 Area (when present)						
None	Urbanization x Ownership		88	3.412	3,80	**0.021**
Publicly-owned, B-D	Urbanization		18	2.556	2,15	0.111
Privately-owned	Urbanization		69	2.133	3,65	0.105
Category B	Ownership		30	0.000	1,28	0.993
Category C	Ownership		26	8.010	1,24	**0.009**
Category D	Ownership		29	0.809	1,27	0.376
Public/Private Combined	Urbanization		72	2.557	3,68	*0.062*
Tier 2 Percent of Total Vacant Land (when Tier 2 land is present)						
None	Urbanization x Ownership		88	1.173	3,80	0.325
None	Urbanization		88	0.064	3,84	0.835
None	Ownership		88	4.361	1,86	*0.076*
Categories B-D	Ownership		85	2.172	1,83	0.144
Public/Private Combined	Urbanization		72	0.382	3,68	0.767
Presence of Tier 3 Land						
None	Urbanization	30.841	97		3	**<0.001**
Categories B-D	Urbanization	2.942	89		2	0.230
None	Ownership	0.002	97		1	0.965
Public/Private Combined	Urbanization	32.921	79		3	**<0.001**
Public/Private Combined, B-D only	Urbanization	3.562	71		2	0.168

TABLE 2.6. Summary of Results

Data Restriction	Effect	Chi-square	N	ANOVA F-Ratio	df	p-value
Tier 3 Area (when present)						
None	Urbanization x Ownership		88	2.994	3,80	**0.036**
Publicly-owned, B-D	Urbanization		18	1.845	2,15	0.192
Privately-owned	Urbanization		69	2.359	3,65	*0.080*
Category B	Ownership		30	0.000	1,28	0.995
Category C	Ownership		26	6.586	1,24	**0.017**
Category D	Ownership		29	0.809	1,27	0.376
Public/Private Combined	Urbanization		72	2.742	3,68	**0.050**
Tier 3 Percent of Total Vacant Land (when Tier 3 land is present)						
None	Urbanization x Ownership		88	0.794	3,80	0.501
None	Urbanization		88	0.202	3,84	0.894
None	Ownership		88	5.658	1,86	**0.033**
Categories B-D	Ownership		89	0.583	1,87	*0.068*
Public/Private Combined	Urbanization		72	0.707	3,68	0.551
Presence of Tier 4 Land						
None	Urbanization	2.899	97		3	0.408
None	Ownership	0.028	97		1	0.868
Public/Private Combined	Urbanization	4.514	79		3	0.211
Tier 4 Area (when present)						
None	Urbanization x Ownership		93	3.527	3,85	**0.018**
Publicly-owned, B-D	Urbanization		19	2.660	2,16	0.101
Privately-owned	Urbanization		73	1.969	3,69	0.127
Category B	Ownership		31	0.121	1,29	0.730
Category C	Ownership		26	6.586	1,24	**0.017**
Category D	Ownership		29	0.938	1,27	0.341
Public/Private Combined	Urbanization		76	1.909	3,72	0.136
Tier 4 Percent of Total Vacant Land (when Tier 4 land is present)						
None	Urbanization x Ownership		93	0.193	3,85	0.901
Publicly-owned, B-D	Urbanization		19	0.015	2,16	0.985
Privately-owned	Urbanization		73	2.446	3,69	*0.071*
Category B	Ownership		31	1.357	1,29	0.254

TABLE 2.6. Summary of Results

Data Restriction	Effect	Chi-square	N	ANOVA F-Ratio	df	p-value
Category C	Ownership		26	0.218	1,24	0.645
Category D	Ownership		29	2.939	1,27	*0.098*
Public/Private Combined	Urbanization		76	2.377	3,72	*0.077*
Presence of Tier 5 Land						
None	Urbanization	5.799	97		3	0.122
None	Ownership	0.968	97		1	0.325
Public/Private Combined	Urbanization	8.989	79		3	**0.029**
Tier 5 Area (when present)						
None	Urbanization x Ownership		95	3.580	3,87	**0.017**
Publicly-owned, B-D	Urbanization		19	2.316	2,16	0.131
Privately-owned	Urbanization		75	1.510	3,71	0.219
Category B	Ownership		33	0.417	1,31	0.523
Category C	Ownership		26	6.456	1,24	**0.018**
Category D	Ownership		29	2.208	1,27	0.149
Public/Private Combined	Urbanization		78	1.225	3,74	0.307
Tier 5 Percent of Total Vacant Land (when Tier 5 land is present)						
None	Urbanization x Ownership		95	0.274	3,87	0.844
None	Urbanization		95	0.909	3,91	0.440
None	Ownership		95	1.254	1,93	0.266
Public/Private Combined	Urbanization		78	1.932	3,74	0.132
Overall land composition						
None	Urbanization x Tier		474	6.441	15,450	**<0.001**
Tier 1	Urbanization		79	1.964	3,75	0.127
Tier 2	Urbanization		79	7.925	3,75	**<0.001**
Tier 3	Urbanization		79	3.075	3,75	**0.033**
Tier 4	Urbanization		79	11.852	3,75	**<0.001**
Tier 5	Urbanization		79	2.658	3,75	*0.054*
Tier 6	Urbanization		79	0.477	3,75	0.699

FIGURE 2.6. Parcel size: Category B (Suburban) parcels by ownership

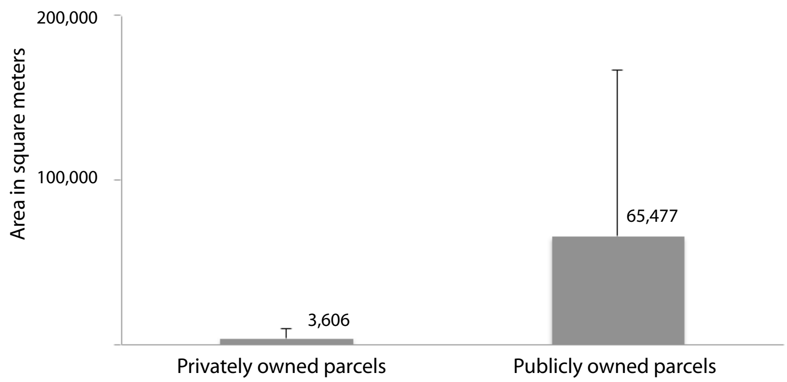


FIGURE 2.7. Presence of vacant parcels: By ownership

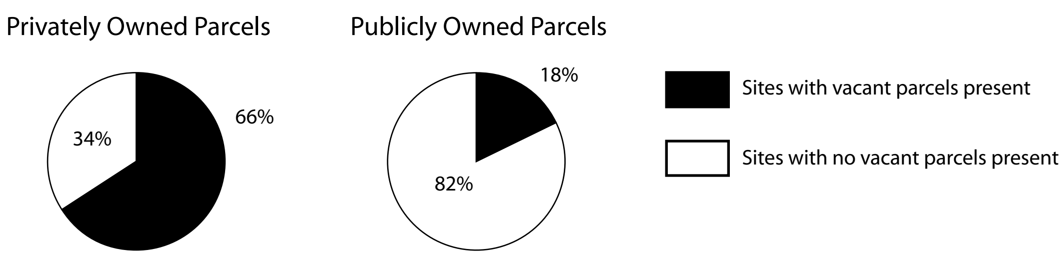


FIGURE 2.8. Vacant area per site, when present: Urban Employment category by ownership

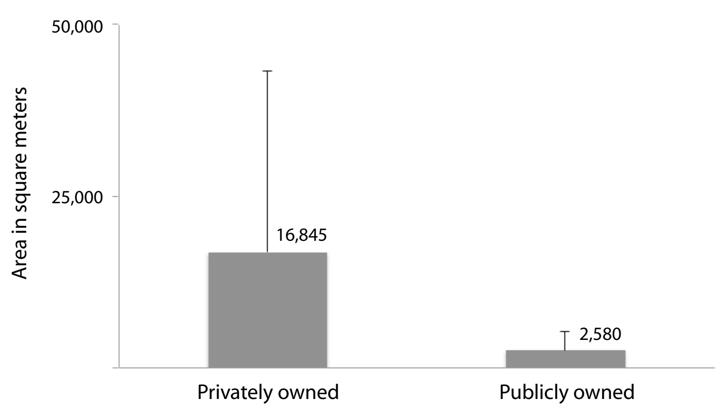
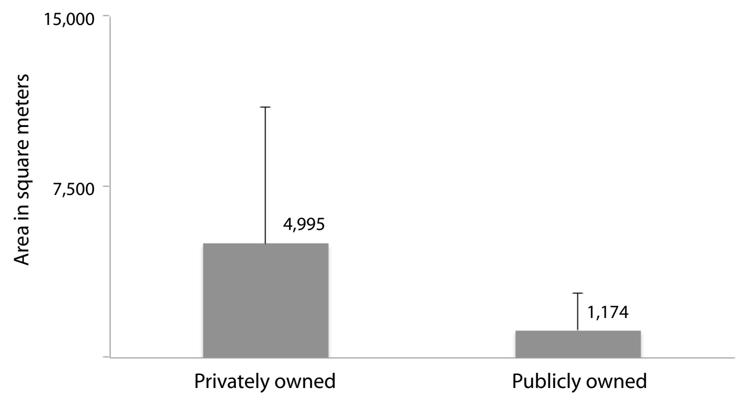


FIGURE 2.9. Vacant area per site, when present: Urban Residential category by ownership



urban contexts. Results support the hypothesis that privately owned land is more plentiful than publicly owned land. Privately owned land is more likely to be present across all categories (χ^2=53.593, df=1, N=232, p=<0.001; Fig. 2.7). In the Urban Employment ($F_{(1,24)}$=6.555, p=0.017; Fig. 2.8) and Urban Residential categories ($F_{(1,28)}$=10.467, p=0.003; Fig. 2.9), it is also likely to occur in greater quantity. This difference was not found in the Suburban category, however ($F_{(1,31)}$=0.316, p=0.578). This result may correspond to the larger parcel size of publicly owned land in that category. Ownership was not found to have an effect on parcel perimeter-area ratio ($F_{(1,95)}$=0.191, p=0.663).

Analysis of the land suitability index also revealed some differences in quality between publicly and privately owned vacant land. Tier 1 land, which had the most stringent criteria, was too sparse to analyze in detail by ownership, but it was no more likely to be present in publicly owned vacant land than in privately owned (χ^2=0.523, df=1, N=97, p=0.470). In the Urban Employment category, privately owned land qualifying for Tier 2 ($F_{(1,24)}$=8.010, p=0.009), Tier 3 ($F_{(1,24)}$=6.586, p=0.017), Tier 4 ($F_{(1,24)}$=6.586, p=0.017), and Tier 5 ($F_{(1,24)}$=6.456, p=0.018) was found to be more plentiful than publicly owned land qualifying for those tiers (Fig. 2.10). These results are consistent with the difference in abundance of vacant land and do not suggest

FIGURE 2.10. Tier 2, 3, 4, and 5 land area per site, when present: Urban Employment category by ownership

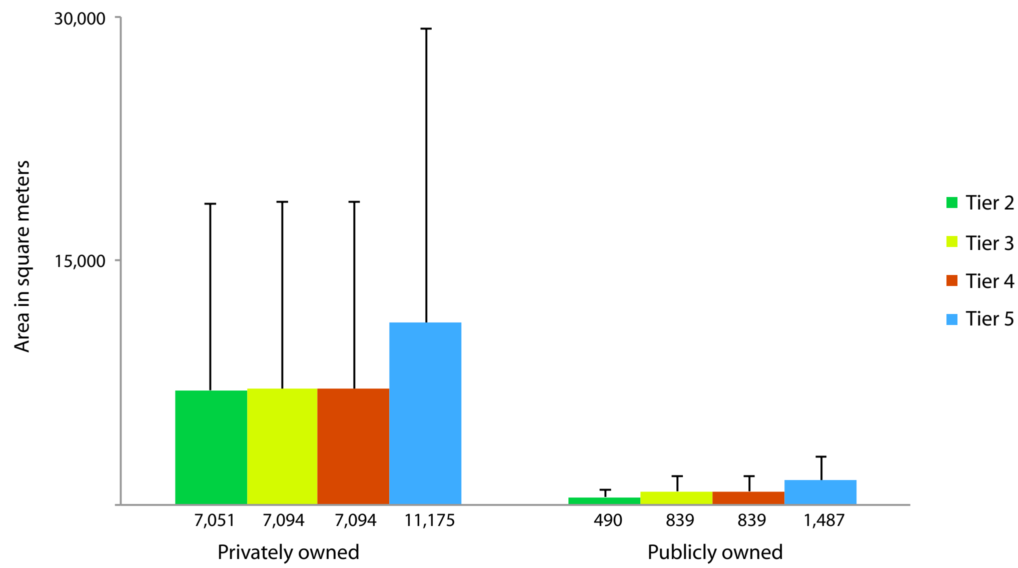
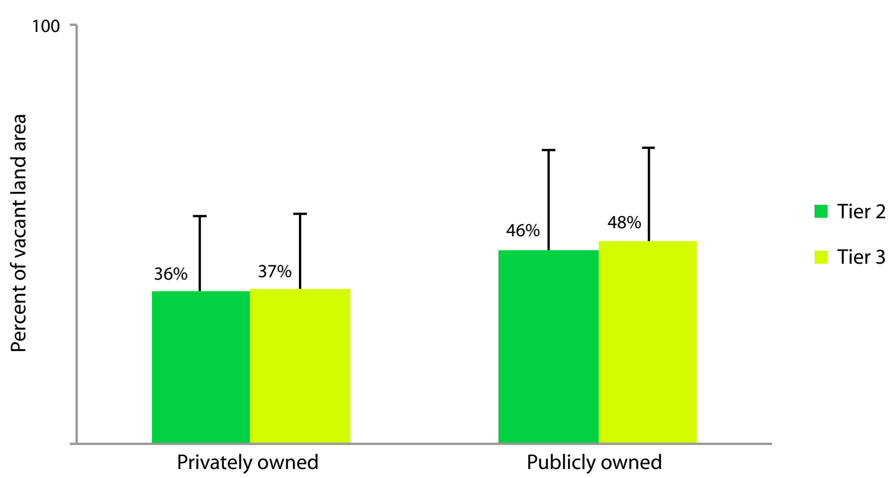


FIGURE 2.11. Tier 2 and Tier 3 percent of total vacant area, when present: By ownership



any actual differences in land composition. In fact, publicly owned land was found to have a higher proportion of land qualifying for Tier 3 ($F_{(1,86)}$=4.695, p=0.033; Fig. 2.11), suggesting that although it is more rare, publicly owned land is of higher quality.

These results support rejection of the null hypothesis stating that "ownership has no effect on vacant parcel size, abundance, or quality."

2.3.2 Differences in vacant land among urban categories

Significant differences were also found in vacant land resources among urbanization categories. Parcels in the Rural category were substantially larger than in the other categories, with parcel size getting progressively smaller in the Suburban, Urban Employment, and Urban Residential categories ($F_{(3,75)}$=6.563, p=0.001; Fig. 2.12). Among privately owned parcels, those in the Rural category were again the largest, but those in the Urban Employment category were larger than those in the Suburban or Urban Residential categories ($F_{(3,72)}$=6.855, p=<0.001; Fig. 2.12). Suburban category publicly owned parcels were larger than publicly owned parcels in the Urban Employment or Urban Residential categories ($F_{(2,17)}$=6.838, p=0.007; Fig. 2.12). Together these results indicate that, excluding the Rural category, publicly owned parcels are largest in the Suburban category, while privately owned parcels may be largest in the Urban Employment category. Private landowners in Urban Employment areas are perhaps more likely to be employers or companies with larger tracts of land, while Suburban landowners are likely to be individual owners of residential parcels. The larger publicly owned parcels in the Suburban category suggest that publicly owned land occurs in larger swaths outside of denser urban contexts. Urbanization was not found to have an effect on parcel perimeter-area ratio ($F_{(3,75)}$=0.646, p=0.588).

The Rural category is significantly less likely than the other categories to have vacant land included in this analysis (χ^2=34.679, df=3, N=116, p=<0.001; Fig. 2.13). In an effort to identify "idle" vacant land not currently in production, this analysis excluded parcels with an

FIGURE 2.12. Parcel size: By urbanization

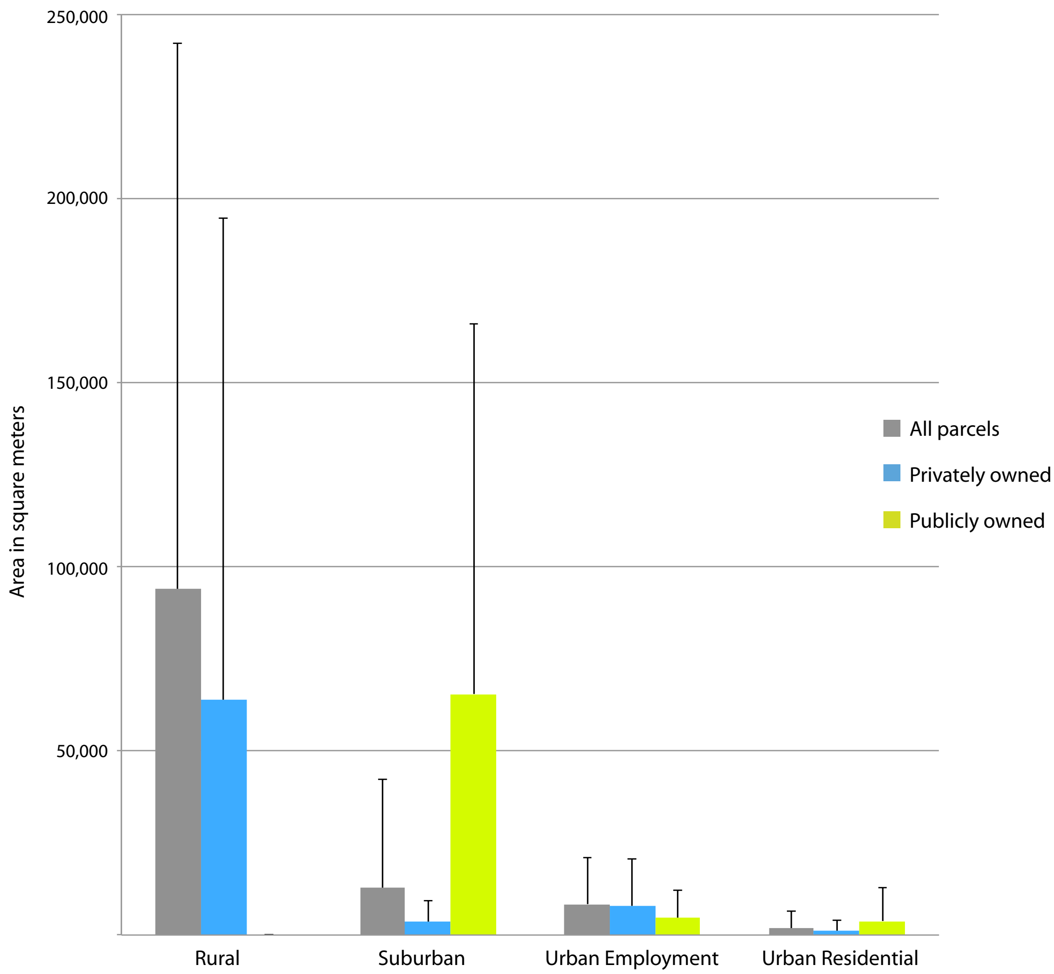
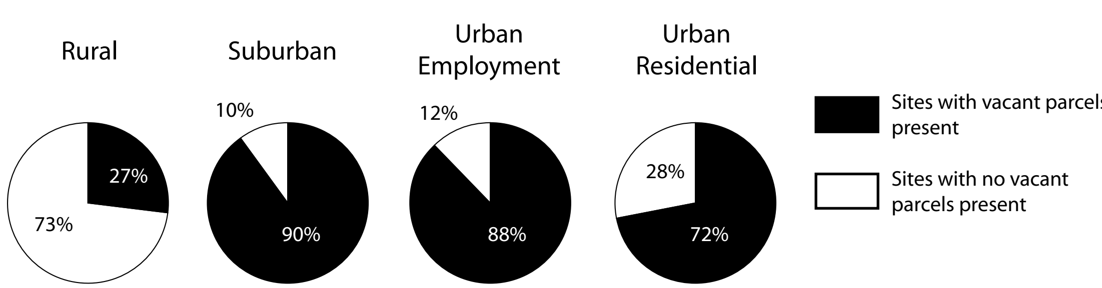


FIGURE 2.13. Presence of vacant parcels: By urbanization



"agricultural vacant" land use class. It is apparent (and not surprising) that when vacant land occurs in this traditionally agricultural setting, it is likely already to be in production, rather than "idle."

Urbanization did not have a statistically significant effect on the presence (χ^2=3.762, df=3, N=79, p=0.288) or amount of land ($F_{(3,9)}$=1.426, p=0.298) qualifying for Tier 1. Tier 2 and Tier 3 land, which has a less stringent soil quality criterion, is less likely to occur in Rural vacant land (χ^2=32.921, df=3, N=79, p=<0.001; Fig. 2.14). When Tier 3 land is present, it occupies larger areas in the Rural category than in the other categories ($F_{(3,68)}$=2.742, p=0.050; Fig. 2.15), with the Urban Residential category having the least area. The occurrence of Tier 4 land was not found to vary according to urbanization (χ^2=4.514, df=3, N=79, p=0.211). Tier 4 broadens the criteria to include parcels without access to public water. Public water access typically corresponds to higher-density, more urban settings, so it is not surprising that broadening the criteria in this way would nullify differences found between the Rural category and other categories under more stringent criteria. Tier 5 land, which broadens previous criteria by including slopes of 5-10%, is less likely to occur in the Rural category (χ^2=8.989, df=3, N=79, p=0.029; Fig. 2.16), but does not vary between categories in terms of area ($F_{(3,74)}$=1.225, p=0.307) or percentage ($F_{(3,74)}$=1.932, p=0.132).

FIGURE 2.14. Presence of Tier 2 and Tier 3 land, when vacant land is present: By urbanization

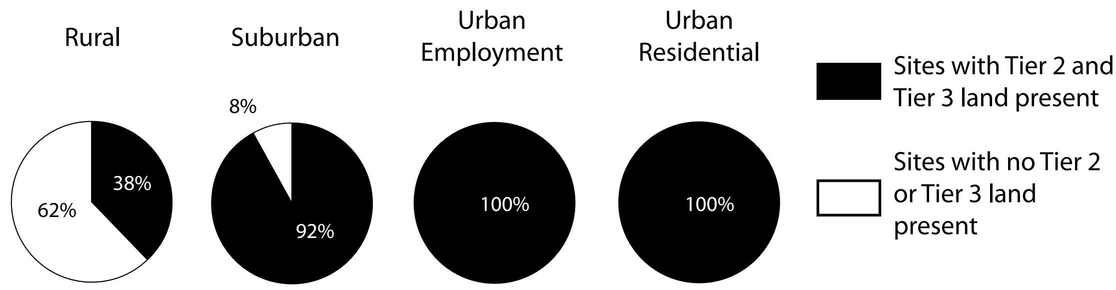


FIGURE 2.15. Tier 3 area per site, when present: By urbanization

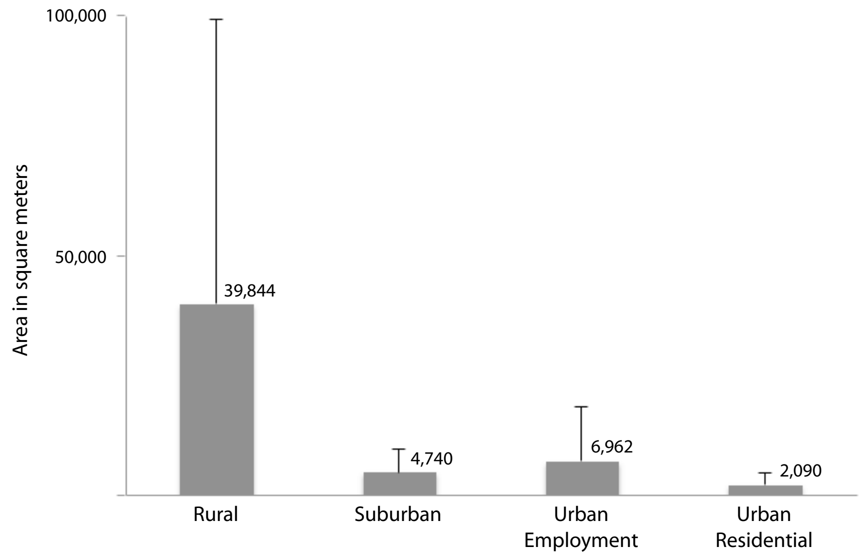


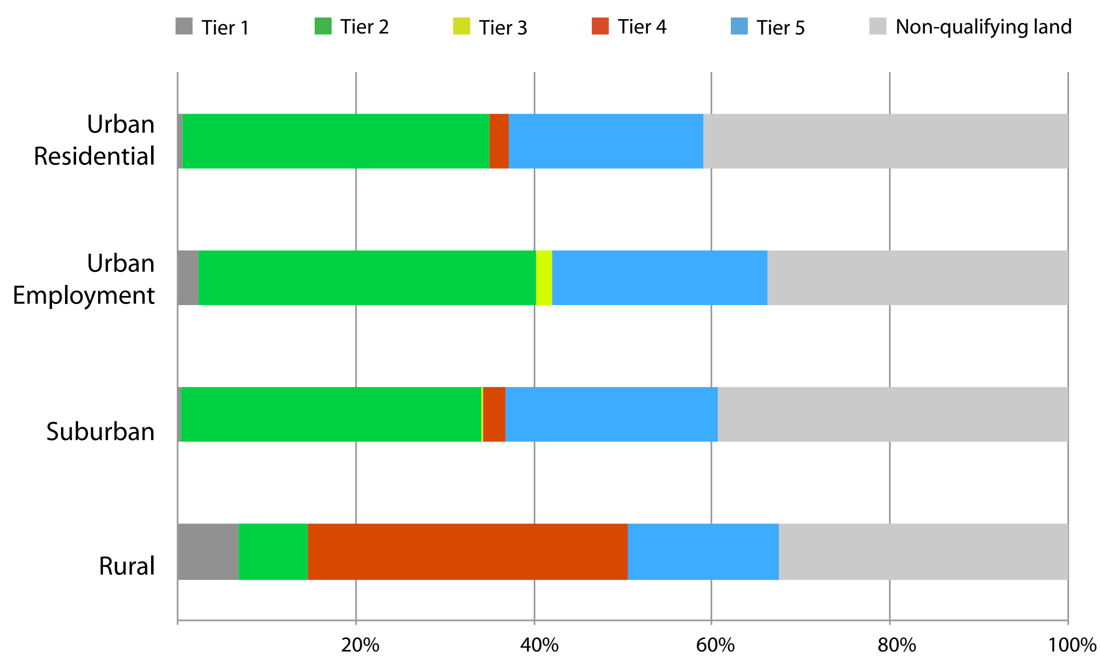
Figure 2.17 illustrates some overall differences in the composition of urban categories

FIGURE 2.16. Presence of Tier 5 land, when vacant land is present: By urbanization

by separating the proportions of land that qualify for each tier. The Rural category has a lower percentage of land qualifying for Tier 2 (but not Tier 1) than the other categories ($F_{(3,75)}$=7.925, p=<0.001), but overcomes this discrepancy with Tier 4 land ($F_{(3,75)}$=11.852, p=<0.001), which composes a higher proportion of land here than in the other three categories. These results indicate that a substantial portion of land in the rural category is limited by access to water, as modeled in this analysis. The Suburban, Urban Employment and Urban Residential categories appear to have roughly similar composition, but the Urban Employment category has a higher proportion of land only qualifying for Tier 3 ($F_{(3,75)}$=3.075, p=0.033) – otherwise suitable land which is limited by very poor soils as modeled by this index.

FIGURE 2.17. Overall land composition: By urbanization

Tiers shown in color had significant differences among urban categories at *alpha*=0.10.



When analyzing results at *alpha* = 0.10, some additional effects emerge. Publicly owned land was found to have a higher proportion qualifying for Tier 2 ($F_{(1,86)}$=3.215, p=0.076; Fig. 2.11). In the Urban Residential category, publicly owned land had a higher proportion of land qualifying for Tier 4 ($F_{(1,27)}$=2.939, p=0.098), indicating that publicly owned land there is less likely to be limited by slopes above 5% or insufficient sun. Publicly owned land occurs in higher amounts in the Suburban category than in the more urban categories ($F_{(2,17)}$=3.199, p=0.066). This result corresponds to the larger parcel size of publicly owned land in the

Suburban category. When Tier 2 land is present, it occupies larger areas in the Rural category than in the other categories, with the Urban Residential category possibly having the least area of Tier 2 land ($F_{(3,68)}$=2.557, p=0.062). Tier 4 land composes a higher percentage of privately owned land ($F_{(3,69)}$=2.446, p=0.071) and all vacant land ($F_{(3,72)}$=2.377, p=0.077) in the Rural category than in the other categories. Land that qualifies for Tier 5 but not Tier 4 composes a smaller proportion of land in the Rural category than the other categories ($F_{(3,75)}$=2.658, p=0.054), suggesting that land in the Suburban, Urban Employment, and Urban Residential categories are more limited by 5-10% slopes.

These results support rejection of the null hypothesis stating that "urbanization has no effect on vacant parcel size, abundance, or quality."

2.4 Discussion

2.4.1 Urbanization categories and sampling

This research compared results according to urbanization categories, which were grouped according to a two-factor PCA based on employment, population, and housing densities. Urban gradient analysis, which has typically been employed in urban ecology studies, creates a gradient from one or more factors and uses that gradient as the basis for analyzing other dependent variables. As the varied approaches to urban gradient analysis demonstrate (e.g. Alberti, 2008; Hahs and McDonnell, 2006), even an empirically based concept of "urban" is neither monolithic nor definitive, and variables used to characterize an urban gradient should be selected on the basis of their relevance to the research question. In this case, population, housing, and employment densities were selected as general indicators of intensiveness of urban land use, as well as for their availability and simplicity of analysis. Because the resulting categories were based on two PCA factors, it cannot simply be said that these categories increase in urbanization from Rural (A) to Urban Residential (D). As the descriptive statistics in Table 2.1 illustrate, "urbanization" in this case increases from Rural to Suburban to Urban Employment and Urban

Residential, with the latter two categories being characterized by highest intensity in employment and population respectively.

Selecting representative sample sites from these categories proved challenging in some ways. Census block groups are the geographical unit of the urban categorization scheme, but 300-meter radius study sites were the ultimate unit of analysis. This boundary discrepancy meant that an individual study site could contain portions of more than one urban category if it fell near a block group border. An arbitrary threshold of 70% composition (of its "home" category) was applied for study site inclusion, but this choice resulted in bias against small block groups of one category surrounded by other categories. The results of this research, however, suggest that the application of an urban gradient to questions of land resources may reveal key differences in vacant land from more to less urban contexts.

2.4.2 Use of publicly available data

This research relied exclusively on publicly available geospatial data for its identification of vacant parcels and for its assessment of land suitability. This data included county parcels, municipal boundaries, SSURGO, LIDAR, DEM, and aerial imagery. Publicly available data offers significant benefits: it provides extensive spatial coverage, is generally easily accessible, and is often of high quality and detail. But these data sources also carry some associated drawbacks—foremost among these is the potential temporal inconsistency within and between datasets. Parcel datasets, for example, are typically updated periodically throughout the year (with varying frequency between counties), whereas the LIDAR and aerial imagery used were from 2006-2010. In some cases, parcel data would classify a parcel as vacant, while older aerial imagery would show it to be built. Such discrepancies are expected when using datasets of different vintage to analyze something as dynamic as the built environment.

Parcel data has been used in other studies to identify vacant parcels for potential food production (e.g. Balmer et al., 2006; Colasanti and Hamm, 2010; Eanes, 2012). Colasanti and

Hamm (2010) cross-referenced a subset of parcels identified as "vacant" against aerial imagery and found a 3.4% error rate. The final cross-check between vacant parcels and aerial imagery in this research turned up a higher error rate of 10.3%, which could be the result of actual inaccuracy in the parcel data and/or a vestige of the span of time between datasets (up to six years between aerial imagery and county parcel data). Aerial imagery was only used to confirm vacancy of parcels categorized as such in the parcel datasets and was not consulted to identify additional vacant parcels not already categorized as vacant. Thus, the vacant land included in this analysis represents a conservative estimate of the actual prevalence of vacant land.

2.4.3 Land suitability index

Previous land inventories have applied various sets of suitability criteria to assess and prioritize land suitable for urban food production. The four criteria included in this research—soil quality, slope, solar exposure, and water access—were selected on the basis of these previous studies as well as conversations with practitioners and the availability of data. This study is the first use of SSURGO data to assess soil quality of land for urban agriculture, and while the SSURGO dataset is extensive and detailed, its accuracy within the urban context should be considered with caution. Federal soil mapping efforts have typically focused only on the agricultural capability of rural soils and the development potential of urban land; furthermore, urban soils can exhibit high variability even on the scale of a single parcel (Shuster et al., 2011). This research also explores the use of LIDAR to assess solar exposure, which to the author's knowledge has not been applied to assessment of land for urban food production, with the exception of Nipen (2009). Although this use of LIDAR requires access to mapping software and some expertise, it may provide a more accurate and feasible method for wide-scale assessment of solar exposure than individual site visits or assessment of aerial images, as have been the norm in previous land inventories. The water access component was a binary rating based solely on access to public water, which in many cases was assumed based on municipal boundaries. Aside from the potential inaccuracy of this assumption, vegetable growers may have access to other sources of water on-site, such as wells or ponds. These other water sources were not accounted for in this analysis.

The four-factor suitability index developed and applied in this research provides a potentially replicable index for other locales but should be checked for accuracy before broader application. In particular, the soil quality and solar exposure components, given their novel inclusion, should be assessed for how well they capture actual conditions. This index should also be approached as an initial assessment and prioritization tool rather than a final selector of parcels. Other characteristics beyond the scope of this research, such as soil contamination, impervious surfaces, and surrounding neighborhood demographics, may all come into play in further assessments of appropriate parcels.

Finally, it should be noted that this assessment of vacant land and its suitability for food production represents a snapshot of dynamic characteristics. Even if perfectly accurate real-time datasets were available for all of the included variables, these datasets would still not capture the ways in which these characteristics change over time. Vacant land becomes built; built land becomes vacant. In the process of these changes, solar dynamics shift, soils become degraded or replaced, and slopes are created or leveled. Further research on the temporal dynamics of vacant land and its characteristics may be highly relevant to practitioners of urban farming and gardening, particularly those utilizing borrowed land on a temporary basis.

2.4.4 Implications and conclusions

The results of this research suggest some key differences in vacant land between urban contexts and according to ownership. The potential implications of these for practitioners and policymakers are noted below.

- *Privately owned land is more plentiful than publicly owned land.* Some studies have focused on the availability of publicly owned land for food production, but this research demonstrates that privately owned land is much more plentiful. Policies that support, facilitate, and incentivize usufruct agreements between landowners and farmers and gardeners may be more successful in maximizing urban food production than simply encouraging use of publicly owned land. Two programs in Ohio (OSU Extension Urban Agriculture program in Cleveland, and Franklin Park Conservatory Growing to Green program in Columbus) provide sample use agreements for gardeners and landowners (Dawson, 2011; Thompson, 2011), but incentives and support at the municipal level could encourage these agreements. The city of Escondido, California, for example, manages an "Adopt-a-Lot" program that facilitates agreements between private landowners and potential users of vacant land. The city provides liability coverage and can waive zoning restrictions that might restrict gardening activities (Buquet, 2011; City of Escondido, 2013).

- *Soil quality is the most crucial obstacle to food production in urban settings.* The Urban Employment and Urban Residential categories show a substantial increase in suitable land area in the transition from Tier 1 to Tiers 2 and 3. Even this finding is based on an optimistic model using SSURGO data, which may overestimate the quality of urban soils. One of the many benefits of urban agriculture is its ability to "close the resource loop" by rerouting urban waste streams to develop soil fertility (Smit and Nasr, 1992). As Beniston (2013) demonstrated, amendment of urban soils with ample compost can greatly increase vegetable productivity. Policies and programs that encourage or enable conversion of organic waste to compost—and make that compost available to urban farmers or gardeners—could greatly increase the area of potential land suitable for food production, while also minimizing landfill waste.

- *Vacant land in high-density residential contexts is rare.* In the Urban Residential category, only 72% of study sites had any vacant land, and those that did had an average of only 2,090 square meters of land qualifying for Tier 3—fewer than any of the other categories. Vacant land in these areas was also more likely to be privately owned. The lack of vacant land in these contexts is particularly notable because it is also these areas—with high populations living in close proximity—where residents are least likely to have access to their own land. If expanding access to the experience of food production is a goal for policymakers, then policies that facilitate usufruct agreements with private landowners and convert waste streams to compost would be particularly crucial and effective in these settings.

Utilization of vacant urban land for food production could increase access to local foods for urban residents while also providing access to land and opportunities for deeper engagement with the food system. By combining urban gradient analysis and land inventory methodologies, this research demonstrates that vacant land resources vary according to urbanization and ownership in terms of abundance and the measures of suitability considered in this study. Policymakers and practitioners who want to expand urban food production could do so more effectively by customizing their approaches to the urban context and by targeting privately owned land as a potential resource.

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